Synopsis for Registration as Research Student

For

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On

Development of Different Deep Learning Techniques for Brain Tumor Analysis

By

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Abstract of proposed work plan

Brain tumor extraction and its analysis are challenging tasks in medical image processing. Brain tumor segmentation consists of separating the different tumor tissues (solid or active tumor, edema, and necrosis) from normal brain tissues: gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF). In brain tumor studies, the existence of abnormal tissues may be easily detectable most of the time. However, accurate and reproducible segmentation and characterization of abnormalities are not straight forward. With the growing extent of aging population, cancer has become a global public health problem.

MRI is a significant diagnostic imaging method, which is employed for the early detection of abnormal changes in tissues and organs and it is a non-invasive imaging technique as well. As the images are inherent in nature, medical image segmentation is a difficult and challenging task. Various methods proposed in the literature have met with only limited success due to overlapping intensity distributions of healthy tissues, tumor and surrounding edema. Moreover the diagnosis requires large data access and hence huge volume of storage as the number of cancer patients recorded are increasing drastically every year. There are number of unidentified types of tumors recorded so far. The medical records and the MR Images of patients need to be transmitted from rural place to the other end for diagnosis, treatment and research.

The brain tumor segmentation is a very difficult and important task which is used in surgical and medical planning and assessments. If experts do the segmentation manually with their own medical knowledge, it will be time-consuming. It creates the need of methods and systems which can do the segmentation automatically.

Magnetic resonance imaging (MRI) is the prime technique to diagnose brain tumors and monitor their treatment. Different MRI modalities of each patient are acquired and these images are interpreted by computer-based image analysis methods in order to handle the complexity as well as constraints on time and objectiveness.

The goal of this topic is to contribute to the medical image segmentation, specifically to the field of brain tumor detection and segmentation using MRI images. Three proposed methods available in the literature are:-1) Fast pathology presence detection approach, which is based on multi-resolution symmetry analysis 2) An unsupervised extraction algorithm of glioma, and 3) A supervised approach of three brain tumor segmentation sub-problems (segmentation of whole tumor, tumor core, and active tumor). Most of the segmentation algorithms require pre-processing technique. In MRI preprocessing, this usually includes spatial co-registration, bias field correction, intensity normalization, and skull stripping.

Challenges in the segmentation of gliomas from MRI data are related to 1) The infiltration of cells into the tissue, introducing unsharp borders with irregularities and discontinuities (a tumor is not necessary a signals connected object), 2) The great variability in their contrast uptake (depending on their vascularisation) and 3) Their appearance on standards MRI protocol with enhanced weighted contrast agent. The majority of the MRI-

based glioma segmentation methods that have been proposed in the literature are region based. Recently, deformable models and edge-based information are used.

Different systems for the MRI data classification have been developed to identify the abnormalities in the brain. To separate the normal images from the abnormal images, normally all the developed systems have the pre-processing, extracting features and classification. Several approaches have been introduced to utilize the machine learning approaches. The previous research works developed the hybrid solutions on the basis of principal component analysis, support vector machine, wavelet transform and independent component analysis. To classify the abnormal and normal brain MRI images, the KNN and feed forward back propagation ANN based classifiers are employed [13]. Previous works that are carried out on this computer aided brain MRI needs to be reviewed to show the importance of processing brain MRIs.

Although there are many approaches are introduced for the brain tumour detection, still now it is a challenging process. Still, a better method is needed for the detection of brain tumours using the MRI images.

The major objective of this work is, effective development of segmentation model using Hybrid Deep neural network with Deer Hunting (HDDH) algorithmto predict brain tumor in MRI images. It also aim to shows that the developed model can be applied to the MRI brain medical databases to predict the data with reasonable accuracy. Also develop an automatic brain tumor segmentation system and also detect the size and location of brain tumor and edemas from magnetic resonances imaging.

1. Introduction

A brain tumor or intracranial neoplasm occurs when abnormal cells from within the brain. There are two main types of tumors: malignant or cancerous tumors and benign tumors. Cancerous tumors can be divided into primary tumors that start within the brain, and secondary tumors that have spread from somewhere else, known as brain metastasis tumors. Diagnosis is usually by medical examination along with computed tomography or magnetic resonance imaging. Brain tumors are not a very common disease, but they are among the most fatal cancers. [1] Reported an incidence of less than 1 h in the western population but life expectancy for an individual can be one year or even less for the most aggressive brain tumors. The causes of brain cancer are still largely unknown, the only environmental risk factors which could be identified so far, are exposure to certain chemicals or ionizing radiation.

In recent medical scanning methods, MRI scanning is identified as a superior one than CT scanning, because various intensity tissues present in brain MRIs have high contrast and sensitivity [1]. Minimum intensity variation exist between tumor cells and surrounding cells makes the task of tumor detection from brain MRIs a difficult one. Glioblastoma and Glioma are the two categories of brain tumours [2]. The Glioblastomatumours are detected with high accuracy level by employing the conventional methods and these are the low pixel intensity cells. In adults, the common brain tumour is Glioma can be classified into four grades. These four grades contains irregular boundary regions and high pixel intensity cells. These cells are developed from the glial cells [3]. Due to the presence of irregular boundaries, the tumor detection process is considered as a difficult task. The Tumor threat relies on the combination of various factors such as the way of size, spreading, and location of the tumour [4].

Malignant and Benign are the two types of brain tumours according to the National Cancer Institute [5]. No huge difference is identified between both healthy and malignant tumor cells.These tumour cells grow quickly and spread to the surrounding cells. Almost they are referred as cancer [6]. Whereas the Benign tumours do not spread and they contains abnormal cells which grow slowly with specified limits. Ependymoma, oligodendroglioma, gliboblastoma and astrocytomas are some of the brain tumours. Using the MRI brain images, the detection of brain tumours is complex and more tedious. In certain tissues, the abnormal accumulation of fluid within the body is called as Edema [7]. Two major aspects are the grade and the type of tumour which select the features for the segmentation process. This is due to the differences in the appearance which may be location, contrast uptake, regularity, shape etc. [8].

The tumour has been categorized into four grades due to the security level. The low-gradeglioma uses grade 1 and 2 and the high-grade glioma uses the grade 3 or 4. The least dangerous tumour in grade 1 are usually linked to the prolonged survival. When seen through a microscope they are gradually grown and also practically they have a usual appearance. For this type of tumour grade the treatment via surgery might be a successful one [9]. The cases of grade 1 brain tumour are named as gangliocytoma, ganglioglioma and Pilocytic astrocytoma. Under a microscopic instrument, Grade 2 tumour looks like anomalous and slowly growing. Some disperse into nearby tissues and repeat occasionally as grade high tumour [10]. A grade 3 tumour is known as malignant, yet normally there is no high contrast

among grade 2 and 3 tumours. This tumour has an affinity to frequently replicate as grade 4 and also it is considered as the supreme malignant tumour [11]. When seen in the microscopic instrument, it quickly duplicates the strange appearance and effectively spread into the nearby tissues. Dead cell zones are presented in the middle of the tumour cells [12].

Magnetic Resonance Imaging (MRI) is widely applied to the examination and assistant diagnosis of brain tumors owing to its advantages of high resolution to soft tissues and none of radioactive damages to human bodies. Integrated with medical knowledge and clinical experience of themselves, the experienced doctors can obtain the sizes, locations, shapes and other pathological characteristics of brain tumors according to the information in MRI images to make scientific and reasonable therapeutic treatment. Such studies are often based on quantitative analysis of anatomical segmentations of brain MR images. However, the large changes in brain shape and appearance associated with development, the lower signal to noise ratio and partial volume effects in the neonatal brain present challenges for automatic segmentation of neonatal MR imaging data [4].

Because there are several MRI examinations for every patient in the whole therapeutic treatment, each of which can give 3-dimensional data in multiple sequences, it is a large amount of data to be dealt with for the doctors. Long-time of hard work will inevitably lead to mistakes in the diagnosis of the tumor contours for the doctors. Moreover, it is subjective for the doctors to determine the state of the diseases according to their medical knowledge and clinical experiences. Therefore, developing an automatic or a semi-automatic computer-aided diagnosis system is meaningful in real medical treatments, which can release the workload of doctors and improve the accuracy by giving objective results [3].

Based on statistics of the Central Brain Tumor Registry of the United States (CBTRUS), brain tumor is one of the leading causes of cancer-related deaths in the United States. It is the second leading cause of cancer-related deaths in children under the age 20 as well as in males ages 0-39. The most common primary brain tumor, brain tumors that begin and tent to stay in the brain, is main in glioma with 34%, however glioma, a broad term including tumors arising from the gluey or supportive tissue of the brain (30% of all brain tumors), represents 80% of malignant tumors making it the most common primary brain tumor causing death .This work is particularly focused on the automatic processing of the volumes with glioma in low and high grades. [45].
The method proposed for brain tumor presence detection is a symmetry based algorithm for the detection of a brain tumor presence in two dimensional MR slice [9][10]. The algorithm uses the fact that brain tumors break the approximate tissue structure symmetry in the left and right hemisphere, which is usual for healthy brains. The proposed method is not sensitive to small deviations from perfect alignment and is able to work correctly even with slight rotation. The proposed method was designed for both axial and coronal planes.[27],[29]. The latter type of features, based on the input image, are not applicable for stand-alone slices since the intensities in such slices varies due to different measurement parameters and equipment, and the intensity normalization is not possible. Random forest (RF) [6] is used as a classification algorithm but another supervised algorithm may be used.

1.1 Brain Tumor Segmentation

The automated brain tumor segmentation is still a challenging task. One of the reasons is tumor's unpredictable properties such as size, shape and location unless the tumor development in time is investigated and images from previous scanning are available. Thus common pattern recognition techniques relying on such properties and widely used for object detection and extraction in both medical and real world images cannot be employed.. This is, on the other hand, the advantage compared to image object detection, e.g. human or car, where the color and the background scene vary. There have been an increasing interest in developing such algorithms and, particularly, the automatic brain tumor segmentation task has recently attracted many computer vision research teams Due to variety of brain tumor types and their manifestation in MR images, most state of- the-art methods focus on most common tumor types, i.e. glioblastoma, or they a require specific training database to deal with a specific tumor type. Only few researchers, e.g. Islam [15], tried to train a developed algorithm on one tumor type and test it on another.

The existing methods are deals with the brain tumor detection and segmentation in MRI images with particular focus on high- and low-grade gliomas. Three methods are available for this purpose. 1) The first method deals with the presence detection of brain tumor structures in axial and coronal slices. This method is based on multi-resolution symmetry analysis and it was tested for T1, T2, T1C and FLAIR images [12], 2) The second method deals with extraction of the whole brain tumor region, including tumor core and edema, in FLAIR and T2 images and is suitable to extract the whole brain tumor region from both 2D and 3D.It also uses the symmetry analysis approach which is followed by automatic determination of the intensity threshold from the most asymmetric parts [41]. 3) The third method is based on local structure prediction and it is able to segment the whole tumor region as well as tumor core and active tumor [24]. This method takes the advantage of a fact that most medical images feature a high similarity in intensities of nearby pixels and a strong correlation of intensity profiles across different image modalities. One way of dealing with – and even exploiting – this correlation is the use of local image patches. In the same way, there is a high correlation between nearby labels in image annotation, a feature that has been used in the "local structure prediction" of local label patches. Convolution neural network is chosen as a learning algorithm, as it is known to be suited for dealing with correlation between features. All three methods were evaluated on a public data set of 254 multisequence MR volumes being able to reach comparable results to state-of-the-art methods in much shorter computing time (order of seconds running on CPU) providing means, for example, to do online updates when aiming at an interactive segmentation[33],[38].

1.2 Tumor detection

The goal of these methods is not the accurate delineation of the tumor boundary, but only fast decision whether the tumor is present together with its location. Such techniques could be used as an initial estimation of the tumor contour which is necessary for some segmentation methods. Saha [17] located tumors in 2D MR images in axial plane using the fast detection of asymmetry by Farjam [10] used template-matching technique for this purpose.

2. Review of Literature and Development in the subject

Azian Azamimi Abdullah, Bu Sze Chize and Yoshifumi Nishio [1] developed an automated detection method for brain tumor using Cellular Neural Network (CNN). For this purpose they combined many templates to obtain the accurate results. Simulation results using the new algorithm prove that brain tumor can be detected in shorter time.

Ishita Maiti and Dr. Monisha Chakraborty [2] have used the technique of Watershed algorithm in combination with Edge Detection operation for the Brain Tumor segmentation of an MRI image. The paper includes Marker based Watershed algorithm. And the Edge detection is carried out by the Canny Edge Detector. The two methods are performed on the HSV Color model of an image. The results have been shown to be very accurate through the paper.

J.Vijay and J.Subhashini [3] have concluded that k-Means Clustering is a recognized as a powerful tool for the detection and extraction of Brain tumor from MRI images. The paper uses pixel-based k-Means clustering technique to achieve the aim. The paper has deduced that unsupervised segmentation methods are better than the supervised methods. This technique is proved to be lesser time consuming and achieves maximum lossless compression. The paper proves this technique to be very efficient.

Anam Mustaqeem, Ali Javed, Tehseen [4] Fatima have concluded that Watershed based segmentation and thresholding based segmentation is a powerful tool for the detection of Brain tumour in MRI images. The paper further contains the analysis of persons suffering and dying from this fatal problem of brain tumour. The main emphasis of the paper lies on the various segmentation techniques. The methodology mentioned in the paper consists of Image Acquisition, Preprocessing, Processing and Post Processing of the input MRI image.

Dibyendu Goshal1, Pinaki Pratim Acharjya [5] have introduced a new technique of Marker Controlled Watershed Algorithm to carry out the segmentation of MRI images. The paper shows how this technique overcomes the problem of over segmentation with watershed algorithm. The detailed algorithm with images at each step has been given the paper.
Bjoern H. Menze, Koen Van Leemput, Danial Lashkari [6], presented a multifractal feature-based brain tumor segmentation method is developed. Brain tumor texture is formulated using a multi resolution-fractal model known as multi fractional Brownian motion (mBm). Detailed mathematical derivation for mBm model and corresponding novel algorithm to extract spatially varying multi fractal features are proposed.

B. Menze, M. Reyes, and K. V. Leemput [7], to evaluate efficacy, tumor segmentation performance using proposed multifractal feature is compared with that using Gabor-like multiscale texton feature. Also, novel patient-independent tumor segmentation scheme is proposed by extending the AdaBoost algorithm. The modification of AdaBoost algorithm involves assigning weights to component classifiers based on their ability to classify difficult samples and confidence in such classification.

Y. Peng, A. Ganesh, J. Wright, W. Xu, and Y. Ma [8], the common approach is to normalize the intensities by standardization or histogram matching algorithm. Considering a stand-alone 2D MR slice, such intensity normalization is impossible due to the lack of information about the tumor size and the slice position. The following steps are used:

- Pathology extraction
- Extension into 3D
- Propagation into neighbor slices.
- Convolution Neural Network (CNN)
- Slice Inference

This architecture is designed to take the advantages of a 2D grid input, which is convenient for image processing. In several recent works [12], [14], 3D filters have been proposed for medical image analysis. However, it was shown by Prasoon [18] that it is still too demanding to be efficiently used in today's computers.

Gooya [4], this author proposes a frame-work for accurate intensity-based segmentation of the developing neonatal brain, from the early preterm period to term-equivalent age, into 50 brain regions. The proposed method is compared to standard atlas-based techniques and improves label overlaps with respect to manual reference segmentations [10],[11].

Atiq Islam, Syed M. S. Reza and Khan M. Iftekharuddin [9], brain tumor MRI images exhibit complex characteristics, such as high diversity in tumor appearance and ambiguous tumor boundaries. To address this problem, this approach proposes a novel automatic tumor segmentation method for MRI images. Work can be done on adding other contextual features to further improve the classification accuracy obtained in this study [25][26].

Davy, M. Havaei, D. Warde-Farley [22] in this section, the method proposed for unsupervised brain tumor locating and extracting is evaluated. This method is based on a novel unsupervised algorithm combining 3D multiresolution symmetry analysis described in Secation and automatic thresholding. The 3D unsupervised brain tumor extraction algorithm was also tested on the whole database of 254 multisequence volumes since it does not require any training phase, and, hence, data partitioning is not necessary[15].

Nelly Gordillo,Eduard Montseny and Pilar Sobrevilla [16] in this section, the method for segmentation of particular structures of the brain tumor, i.e. whole tumor, tumor core, and active tumor, is evaluated. This method is based on an approach, whose novelty lies in the principled combination of the deep approach together with the local structure prediction in medical image segmentation task [27],[28].

J. Festa, S. Pereira, J. A. Mariz[34], this paper presents a semiautomatic segmentation system exploiting the superior image quality of ultrahigh field MRI. The proposed approach utilizes the complementary edge information in the multiple structural MRI modalities. It combines optimally selected two modalities from susceptibility-weighted, T2-weighted, and diffusion

MRI, and introduces a tailored new edge indicator function. The goal of image segmentation is to divide an image into a set of semantically meaningful, homogeneous, and non-overlapping regions of similar attributes such as intensity, depth, color, or texture. The segmentation result is either an image of labels identifying each homogeneous region or a set of contours which describe the region boundaries [8],[26].

P. Dvorak, W. Kropatsch, and K. Bartusek [20], the histogram of a bias corrected brain MRI in the presence of noise can be described with a Gaussian mixture model (GMM), where each tissue class (WM, GM, and CSF) is modeled by a Gaussian distribution [20]. The following steps used:-

- Removal of Nonbrain Tissue
- Surface-Based Methods
- Active Contours and Surfaces

Deformable models are also called active contours or snakes in 2D and active surfaces or active balloons in 3D. Deformable models were introduced by Kass[23],[24] in 2D space and were further developed and generalized in 3D space by Terzopoulos[27],[29].

The method was designed for both axial and coronal planes. It is a supervised classification algorithm, which uses features extracted from multi resolution asymmetry maps and, in case of application to particular slices in 3D volume, input slices. Random forest (RF) [1] is used as a classification algorithm but another supervised algorithm may be used.

- Symmetry analysis
- Multi resolution approach
- Unsupervised brain tumor extraction

Application to 3D volumes:-

The proposed algorithm may also be applied to particular slices in 3D volumes. In this case, additional set of features can be extracted. This feature set assumes that the intensities of the input volume have been normalized. The features are as follows:

• Average intensity in the whole masked region,

• Absolute value of the average intensity difference in the left and right masked region,

• Intensity standard deviation in the whole masked region,

• Absolute value of the intensity standard deviation difference in left and right masked region. All of these features are computed for both absolute & relative value threshold [13][17].

Rajesh C. Patil and Dr. A. S. Bhalchandra [41] have analyzed that processing of MRI images is the most challenging and emerging field. Magnetic Resonance Imaging (MRI) is an advanced medical imaging technique used to produce high quality images of the parts contained in the human body. The paper brings out the methodology, which includes preprocessing of the given MRI image, its segmentation and lastly morphological operations on it, for the detection and extraction of brain tumor of real time patient's MRI scan images.

Automated brain tumour detection using discriminative clustering based MRI segmentation was introduced by AbhilashPandaet al. [51]. In this work, they have used discriminative clustering which gives better variance in tissues of brain MRI image and AdaBoost was pretty simple to classify the image as normal or abnormal. Simple linear iterative clustering method also used for generating 2D super pixels. This method achieved better accuracy on Brain Web MRI dataset.

Brain Tumour Detection Using Cuckoo Search Algorithm and Histogram Thresholding for MRI images was proposed by SudeshnaBhakat and SivagamiPeriannan [52]. The system proposed in this work was effective in extracting the tumour part and it has given a careful division of the tumour limit, alongside right visual area of the tumour with the support of the boundary. By using the tumour's size they analyzed that the tumour was actually present or not.

Shiv NareshShivhare et al. [53] introduced an efficient brain tumour detection and segmentation in MRI using parameter-free clustering. For detecting the brain tumour, based on parameter free clustering, morphological dilation and hole-filling operations, they proposed an automatic system.

B. Srinivas and G. Sasibhushana Rao [54] have proposed Fuzzy C Means Segmentation and Support Vector Machine Classification for MRI brain tumour. They used Fuzzy C-means algorithm to detect the tumour and extract it. They evaluated the parameters such as Peak Signal to Noise Ratio (PSNR), Mean Squared Error (MSE) and segmented area.

2 Objectives of Research

In the literature survey, various segmentation techniques used in medical image segmentation are discussed. Threshold based techniques, Region based techniques, Edge based techniques, and Pixel classification techniques are discussed. The available segmentation methods have some limitation.

Listed below are the limitations of the Current Segmentation and Detection methods:

- Automatic, accurate, fast tumor segmentation yet not developed.
- K-means clustering are many iterative rounds may be required.
- Early detection of brain tumors is difficult because the brain is covered by the skull and brain tumors do not exhibit very special clinical symptoms.
- Patch Based:- This method basically works on the similarity between images or sub images, represented by a weighted graph or as sparse matrix [4] computed from intensity-based distance between patches or group of pixels or pixel-level groups [5] defined. This methods is used for labeling [6] human brain as it is easy to implement.
- Overlap of tissues in an iterative manner with shortest distance.
- The segmentation, detection, and extraction of infected tumor area from magnetic resonance (MR) images are a primary concern but a tedious and time taking task performed by radiologists or clinical experts, and their accuracy depends on their experience only.

- Fuzzy K-means methods are unsupervised methods for the data analysis and construction of the model and it's not effective and time consuming method.
- Watershed segmentation method gives over segmentation.
- Segmentation of Brain MR Images through a Hidden Markov Random Field Model and the Expectation-Maximization Algorithm used, the method requires estimating threshold and does not produce accurate results most of the time.
- Few techniques are limited to a single feature input.

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In order to tackle the limitations, the following objectives are derived:

The major objective of this work is, effective development of segmentation model using Hybrid Deep neural network with Deer Hunting (HDDH) algorithm to predict brain tumor in MRI images. It also aim to shows that the developed model can be applied to the MRI brain medical databases to predict the data with reasonable accuracy.

Few major ideas that are applied to achieve the above said objectives are listed below:

- To identify the well suitable segmentation model which can assist the clinical experts in predicting the brain tumor using various psychological and physical attributes.
- To predict the future outcomes based on previous experiences and present conditions.
- To identify the patients at risk, with the aim of increasing quality of care and to reduce the cost of care.
- To undertake study of different segmentation and detection of brain tumor segmentation.
- To develop brain tumor segmentation method.
- To use of Computer aided technology becomes very necessary to overcome these limitations.
- To develop different modules which can compose a comprehensive clinically oriented framework for analyzing tumor-bearing brain images automatically.
- To study of state of art Computer Aided Diagnoses systems used for detection of brain tumor in context of current technologies.
- The Classifier is used to improve the accuracy of the classification of the present work, we are planning to investigate the selective scheme of the by combining more than one classifier and feature selection techniques.
- To solve over segmentation using topological gradient.
- To improve the accuracy within less time.
- To develop more accurate, efficient as well as faster method for early segmentation and detection of brain tumors.

Clustering is the task of grouping a set of objects in such a way that objects in the same group are more similar in some sense to each other than to those in other groups . In this we are going to develop an algorithm to divide an image into separate classes for generating meaningful description. The algorithm is unsupervised and based on features. Once the algorithm is designed, comparison is to be done with all available algorithm for clustering like the unsupervised algorithm Fuzzy C-Means (FCM), k-means, Markov Random Fields (MRF),Brain tumor presence detection, unsupervised brain tumor extraction, segmentation,

detection also the supervised methods which include Bayes and Artificial Neural Networks (ANN) and CNN to prove this algorithm gives efficient results.

Contour refinement algorithm is used to improve the contour of the initial tumor region, to reduce the error determination and missing points near the border, finally to obtain the final results of tumor detection. The key function of preprocessing is to improve the image in ways that increase the chances for success of the other processes. Preprocessing typically deals with techniques for enhancing contrast, removing noise, and isolating regions. This will include the combination of algorithms based on noise removal and the image intensities standardization.

3 Methodology to be Adopted

Work plan:

Input MRI brain image is preprocessed (back ground removal, resize)and then filter with the *Fast Averaging Peer group (FAPG) filter filtering* technique.In addition, classification can be heavily disturbed by skull as the gray level distribution of both skull and tumor are similar. To ensure the excellent performance, a novel method for skull removal is proposed. The background needs to be completely removed from image, so the outliers at theimage boundaries are taken as skull elements. These elements are then automatically selected as seed to recognizethe region growth by removing the skull from MRI.

In the next step, skull removed image is to be segmented with *Multilevel Threshold based Social Ski-Driver (MTSSD) optimization*.Furthermore, from the segmented images*hybrid features*, including gray-level co-occurrence matrix (*GLCM*), pyramid histogram of the oriented gradient (*PHOG*), modified completed local binary pattern (*MCLBP*), and intensity-based features are extracted together from the filtered images. After that*, Adaptive Sun Flower Optimization (ASFO) algorithm* is used to select the optimal features from the extracted hybrid features. At last, the tumors are detected based on the selected features only using *Hybrid Deep neural network with Deer Hunting (HDDH) algorithm*. In addition to that grade of the tumor is detected using convex criteria.

The HDDH is also crucial since it is contributing to the better fitness function value. Optimization of weight has the capability of significantly converge to the optimal or near optimal solution. Due to that, Deer Hunting (DH) has the fastest convergence rate and the possibility of scapping local minima. Basically, the training process of Deep Neural Network (DNN) involves with deciding the connection weights between the neurons to minimize the error. Here, an adaptive sunflower optimization (ASFO) is proposed to identify the global optimum and also to prevent the solution without getting stuck within a local optimum. ASFO is a population-based iterative heuristic global optimization technique which accurately extract the optimal features from the filtered images for the sake of accurate segmentation and classification.

- It is proposed to establish the need of tumour segmentation and detection through literature review and medical survey.
- Identify the required methods that can be used for implementing brain tumour segmentation and detection algorithms.
- The proposed methodology will be fully automatic, initially the pre-processing techniques will be implemented to improve the image quality and to obtain the desired results.
- This technique will be implemented in the working platform of PYTHON and the performance of our proposed system will be compared with the existing technique to prove our system's effectiveness.
- Implementing application of Segmentation for the medical application and testing.

5. Importance of Society application

With the growing extent of aging population, cancer has become a global public health problem. According to the World Cancer Research Fund's latest statistics, cancer is the world's first cause of death. In the worldwide each year, 12.7 million people are diagnosed with cancer, and 7.6 million people died of cancer [8]. Meanwhile, the annual incidence of cancer continues to rise. Every year there will 26 million new cases, and the death tumor will reach to 1.7 million people.

There are several MRI examinations for every patient in the whole therapeutic treatment, each of which can give 3-dimensional data in multiple sequences; it is a large amount of data to be dealt with for the doctors. Long-time of hard work will inevitably lead to mistakes in the diagnosis of the tumor contours for the doctors. Moreover, it is subjective for the doctors to determine the state of the diseases according to their medical knowledge and clinical experiences. Therefore, developing an automatic or a semi-automatic computer-aided diagnosis system is meaningful in real medical treatments, which can release the workload of doctors and improve the accuracy by giving objective results. This is an attempt to bring those cases in to research and helping out for better detection techniques.

6. Proposed work Plan

The approximate duration proposed to complete research project in 36 months. Presentation will be done after every 6 months

- Literature review-after 6 months and Implementation of basic preprocessing algorithms to improve the image quality.
- Implementation of available segmentation algorithms and proposed segmentation algorithms.
- Implementation of algorithm for contour delineation detecting the size of tumor.
- Implementation of algorithm for segmentation and tumor detection.
- Comparing the results obtained from proposed and existing segmentation algorithm.
- Creating an application of Segmentation for medical application and testing.

Final submission of thesis will be after permission of guide and fulfilling minimum requirements.

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